On the opportunity cost of crop diversification

On the Opportunity Cost of Crop Diversification

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[Original submitted April 2017, Revision received October 2017, Accepted January 2018]

Abstract

Distance functions are increasingly being augmented, with environmental goods treated as conventional outputs. A common approach to evaluate the opportunity cost of providing an environmental good is the exploitation of the distance function's dual relationship to the value function. This implies that the opportunity cost is assumed to be non-negative. This approach also requires a convex technology set. Focusing on crop diversification for a balanced sample of 44 cereal farms in the East of England for the years 2007-2013, this paper develops a novel opportunity cost measure that does not depend on these strong assumptions. We find that the opportunity cost of crop diversification is negative for most farms.

Keywords biodiversity, CAP greening measures, Shannon index, non-convexity, shadow price, duality, crop diversification

JEL code D22, D24, D92, Q12, Q51

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1. Introduction

Agriculture not only provides economic outputs, but also generates externalities including environmental goods (*e.g.,* landscape conservation and habitat for birds) and 'bads' (*e.g.,* nitrogen and phosphorus surplus due to fertiliser use). Environmental goods and bads are non-marketed, and may call for government intervention to deal with or internalise these external benefits and costs to align consumers' and producers' interests (Areal, Tiffin et al., 2012). A large body of economic literature assesses the trade-off between production and externalities. Externalities have commonly been implemented in a distance function framework, to estimate environmental efficiency and productivity measures. The shadow price of an externality can be computed by exploiting the distance function's dual relationship to the value function. Knowing the shadow price of an externality is useful for policy makers, who may set up schemes to compensate for the potential financial losses incurred by the farmers.

Studies originally focused on environmental bads. Examples in the agricultural sector include nitrogen surplus (Piot-Lepetit and Vermersch, 1998; Reinhard, Lovell et al., 1999; Piot-Lepetit and Le Moing, 2007), phosphorus surplus (Reinhard, Lovell et al., 2000; Coelli, Lauwers et al., 2007), pesticide pollution (Oude Lansink and Silva, 2004; Chambers, Serra et al., 2014; Serra, Chambers et al., 2014) and greenhouse gas emission (Oude Lansink and Silva, 2003; Dakpo, Jeanneaux et al., 2017).

The literature has increasingly identified an interest in augmenting distance functions with environmental goods. To the best of our knowledge, Färe, Grosskopf et al. (2001) are the first to adopt this approach, focussing on non-marketed characteristics of conservation land in the United States. Other studies extend the distance function with the extent of wetland and interior forest (Macpherson, Principe et al., 2010), six key indicators of biotic integrity of watershed data (Bellenger and Herlihy, 2009; Bellenger and Herlihy, 2010), the extent of permanent grassland (Areal, Tiffin et al., 2012), cultural services, biodiversity, carbon sequestration and the extent of arable and grassland (Ruijs, Wossink et al., 2013; Ruijs, Kortelainen et al., 2017), the Shannon index for crop diversity (Sipiläinen and Huhtala, 2013), and wetland quality (Bostian and Herlihy, 2014). Färe, Grosskopf et al. (2001), Bellenger and Herlihy (2010), Ruijs, Wossink et al. (2013), Sipiläinen and Huhtala (2013), Bostian and Herlihy (2014) and Ruijs, Kortelainen et al. (2017) compute the shadow price of their environmental goods by exploiting the output distance function's dual relationship to the revenue function.

These studies' distance function approach has two important limitations, which can lead to an incorrect assessment of the opportunity cost of the considered environmental good. First, it is assumed that an environmental good can be treated as a conventional, strongly disposable output and that its shadow price is consequently always non-negative. Second, it is necessary to assume that the augmented environmental technology set is convex, to ensure that the distance function's dual relationship to the value function holds.

Both assumptions are very strong. The strong disposability assumption implies that the provision of an environmental good is assumed to be non-increasing for increases in the output level. However, several contributions argue that some environmental goods are complementary to conventional production for lower levels of the environmental good, and competitive for higher levels (Harvey, 2003; Hodge, 2008). This means that the shadow price of an environmental good could also be negative. Such a complementary-competitive relationship is hypothesized for *inter alia* the environmental quality of grassland and livestock production (Vatn, 2002), pollinator habitat and crop production (Wossink and Swinton, 2007), and the entire ecosystem on the farm and total agricultural production (Hodge, 2000). The strong disposability assumption also implies that the provision of an environmental good is assumed to be non-decreasing for increases in the input level. As shadow-pricing of environmental goods inherently focuses on the trade-off between the environmental good and the conventional output, this has generally been left undiscussed by the literature. However, there is no theoretical reason to assume this *a priori*. Ruijs, Wossink et al. (2013) and Ruijs, Kortelainen et al. (2017) seem to be the only authors that check the transformation function empirically and confirm the theorised relationships. Nonetheless, this remains a contested assumption for which the theoretical basis is lacking and the evidence is scarce. We believe that this assumption is especially problematic for inputs that increase the provision of environmental bads such as pesticides and fertilisers.

More and more studies argue that the environmental technology set is non-convex (Di Falco and Chavas, 2009; Chavas and Di Falco, 2012). The convexity assumption is invoked for analytical rather than theoretical reasons (Pope and Johnson, 2013). Again, Ruijs, Wossink et al. (2013) and Ruijs, Kortelainen et al. (2017) seem to be the only authors that empirically test the convexity assumption. They do not find evidence of convexity. This implies that their resulting opportunity costs do not maximise benefits and should not be used to design a pricing mechanism.

We focus on the Shannon index for crop diversity. This index was also the focus for Sipiläinen and Huhtala (2013), who computed its shadow price using the dual relationship of the distance function to the revenue function. Crop diversity has been shown to be linked with *inter alia* long-term stability of the carbon stock in the soil (Henry, Tittonell et al., 2009), improved nutrient balance (Pimentel, Hepperly et al., 2005) and landscape diversity (Westbury, Park et al., 2011). In the context of crop production, it measures the crop diversity by representing the number of crop types and evenness of the area covered by the crops. Considering the number of crop types as well as evenness, the Shannon index for crop diversity is an essential determinant of sustainable food supply (Aguilar, Gramig et al., 2015). From an ecological perspective, it is thus important to increase the Shannon index for crop diversity. Various studies in the economics literature use the Shannon index for crop diversity as an environmental good (e.g., Weitzman, 2000; Di Falco and Chavas, 2008; Sipiläinen and Huhtala, 2013).

Correct assessment of the opportunity cost of crop diversification is also relevant given the 'Green Direct Payment' measure introduced recently in 2015 by the European Common Agricultural Policy (CAP), which holds for all member states of the European Union. This measure links thirty percent of the direct payments to the provision of environmental goods. One condition for receipt of these payments is the '2 or 3 crop rule' (European Parliament, 2013). This regulation imposes minimum requirements on the number of crops and their proportional cover, which is conceptually in line with the Shannon index for crop diversity. Farms of 10-30 ha should grow at least two crops, with the main crop covering at most 75% of the arable land. Farms larger than 30 ha should grow at least three crops, with the main crop covering at most 75% of the arable land, and two crops covering a maximum of 95% of the arable land. In summary, the Shannon index for crop diversity is relevant in terms of both ecological benefits and policy.

Given the theoretical concerns of shadow-pricing environmental goods using the distance function approach, we compute the opportunity cost of crop diversification in a novel way. Our proposed method is conceptually straightforward. If we use a credible assumption of economic behaviour and its corresponding Shannon index for crop diversity, we can accurately compute the opportunity cost of crop diversification. Such an approach separates the environmental good from the production technology and does not necessarily require a convex technology set, thus overcoming the axiomatic problems associated with shadow-pricing using the distance function approach.

We operationalise our proposal using recent methodological developments in the literature. Cherchye, De Rock et al. (2017) show how one can take into account the output-specific character of inputs and the extent to which reallocation of these inputs over outputs can increase efficiency. We adapt their input distance function framework to Ang and Oude Lansink (2017)'s dynamic profit-maximisation framework and focus on the optimal reallocation of output-specific land use. Using a nonparametric model, we assess the extent to which reallocation of land use can increase current-value profit. We express the opportunity cost of increasing the Shannon index for crop diversity in terms of foregone current-value profit. Doing so allows us to calculate the opportunity cost of crop diversification in a way that avoids implementing the environmental good in the technology set and thus imposes less stringent assumptions on the axiomatic properties of the technology set. Our proposed approach is consistent with the behavioural assumption of dynamic profit-maximisation. Finally, we are able to assess the extent to which farmers would have complied with the CAP's novel '2 or 3 crop rule' should they have optimally reallocated their land use. The application focuses on a balanced sample of 44 cereal farms in the East of England for the years 2007-2013.

The remainder of this paper is structured as follows. The next section explains our method. This is followed by a description of the data. The results are presented and discussed in the subsequent sections. The final section concludes.

2. Method

Following Ang and Oude Lansink (2017), farms are faced with a dynamic, intertemporal profit-maximisation problem where they are price takers in competitive input, output and capital markets, and have identical, static expectations on the discount and depreciation rates. It is assumed that the farms maximise the discounted flow of profits over time at any base time period, while being restricted by the adjustment-cost technology. The latter assumption coincides with the perspective that farms cannot instantaneously adjust quasi-fixed inputs to their long-term optimal levels and investments are coupled with adjustment costs (Silva and Stefanou, 2003; Silva, Oude Lansink et al., 2015). The (variable) intertemporal profit-maximisation problem is (Ang and Oude Lansink, 2017):

$$(1)\ W(p, K_t, w, c) = \max_{\{y(.),x(.),I(.)\}} e^{-r(s-t)} \int_t^{+\infty} [p'y(s) - w'x(s)]\, ds$$

s.t.

$$(2)\ \frac{dK(s)}{dt} = I(s) - \delta K(s) \text{ with } K(t) = K_t$$

$$(3)\ \vec{D}_T\big(y(s), x(s), I(s), K(s), G(s), L(s);\ g_y, g_x, g_I\big) \geq 0 \text{ with } s \in [0, +\infty[$$

where $W(.)$ is the current value form of dynamic profit-maximisation, $y \in \mathbb{R}_+^M$ is the crop output vector, $x \in \mathbb{R}_+^N$ is the variable input vector, $K_t \in \mathbb{R}_+^F$ is the initial capital stock vector, $I \in \mathbb{R}_+^F$ is the investment vector, $L \in \mathbb{R}_+^M$ is the crop-specific land vector, $G \in \mathbb{R}_+^Z$ is the vector of non-reallocatable fixed factors, $p \in \mathbb{R}_{++}^M$ is the vector of output prices, $w \in \mathbb{R}_{++}^N$ is the vector of input prices, $r > 0$ is the rental rate, δ is a diagonal $F \times F$ matrix of depreciation rates $\delta_f >$

$0, f, \dots, F$ and $\vec{D}_T(.)$ is the dynamic directional distance function with the corresponding directional vector in terms of outputs, inputs and investments (g_y, g_x, g_I). Eqs. (2) and (3) denote the equation of motion and the dynamic technology, respectively. For a full characterization of the dynamic directional distance function (extended with the net investment vector), we refer to the appendix of Ang and Oude Lansink (2017).

In line with Cherchye, De Rock et al. (2013) and Cherchye, De Rock et al. (2017), we make a distinction between *joint* and *output-specific* inputs. A joint input cannot be allocated to one specific output and is thus needed for the production of multiple outputs. An output-specific input is allocated to one particular output. Variable and fixed non-reallocatable inputs are joint inputs. Land is our considered output-specific input. This approach is a more realistic representation of the production technology and allows for increased detection of non-maximising farms.

Omitting the time indicators for simplicity, the current-value formulation of Eqs. (1) – (3) is (Ang and Oude Lansink, 2017):

$$(4)\ rW(p, K, w, c) = \max_{\{y,x,I\}} \{p'y - w'x + W_K(p, K, w, c)'(I - \delta' K)\}$$

s.t.

$$(5)\ \vec{D}_T(y, x, I, K, G, L;\ g_y, g_x, g_I) \geq 0$$

where $W_K(.)$ is the shadow value of capital. $W_K(.)$ indicates the increase in current-value profit for a one-unit increase in net investment. It is an implicit, endogenous variable. Nonetheless, as all input prices and output prices are known, we can obtain farm-specific values for $W_K(.)$ by solving a minimax problem following Kuosmanen, Kortelainen et al. (2010) (see Appendix A). In what follows, we operationalise Eqs. (4) – (5) using a nonparametric approach. We note that the empirical analyst may also opt for a parametric approach, which can be more convenient for statistical comparisons. However, this requires a specification of the functional form, which is prone to violations of regularity conditions. The nonparametric approach does not violate any regularity conditions by construction, not requiring any specification of a functional form. In addition to these general remarks, a nonparametric approach is very suitable for this application in particular. First, our paper focuses on computing farm-specific opportunity costs of crop diversification rather than coefficients or elasticities. Second, there are several recent methodological advances in the nonparametric literature, apt for this application. By specifically characterising the inputs as output-specific or joint, and allowing for reallocation possibilities of output-specific inputs (in our case land use), one can model the production process on the farm in a detailed way.

We assume that the production technology satisfies the standard properties of closedness, boundedness, strong disposability of inputs, outputs and investments, and variable returns to scale (see e.g. Färe and Grosskopf, 2005). The benchmark scenario (A) is solved for each farm $j \in \mathbb{R}_+^J$:

$$\text{(A)} \qquad rW(p,w,K,c)^{(1)} = \max_{\{y,x,I,\gamma\}} \{p'y - w'x + W_K(.)'(I - \delta K)\}$$

s.t.

$$\text{(A.1)} \qquad y_m \leq \sum_{j=1}^{J} \gamma_m^j y_m^j, m = 1, \dots, M$$

$$\text{(A.2)} \qquad \sum_{j=1}^{J} \gamma_m^j x^j \leq x_n, m = 1, \dots, M, n = 1, \dots, N$$

$$\text{(A.3)} \qquad \left(I_f - \delta_f K_f\right) \leq \sum_{j=1}^{J} \gamma_m^j \left(I_f^j - \delta_f K_f^j\right), m = 1, \dots, M,\ f = 1, \dots, F$$

$$\text{(A.4)} \qquad \sum_{j=1}^{J} \gamma_m^j G^j \leq G_z, m = 1, \dots, M,\ z = 1, \dots, Z$$

$$\text{(A.5)} \qquad \sum_{j=1}^{J} \gamma_m^j L_m^j \leq L_m, m = 1, \dots, M$$

$$\text{(A.6)} \qquad \sum_{j=1}^{J} \gamma_m^j = 1, m = 1, \dots, M$$

$$\text{(A.7)} \qquad \gamma_m^j \geq 0, m = 1, \dots, M, j = 1, \dots, J$$

where $\gamma_m^j \in \mathbb{R}_+^M$ are output-specific intensity weights. (A.1), (A.2), (A.3), (A.4) and (A.5) impose strong disposability on the inputs, outputs, net investments, non-reallocatable fixed inputs and reallocatable fixed inputs. (A.6) imposes variable-returns-to-scale. (A.7) ensures non-negativity of the intensity weights. The fixed factors are not included in the objective function, but affect current-value profit through the intensity weights γ_m^j in the constraints.

Following Färe, Grabowski et al. (1997), Ang and Kerstens (2016) and Cherchye, De Rock et al. (2015); Cherchye, De Rock et al. (2017), the preceding intertemporal profit-maximisation problem can also be adapted to programme (B) where land use L_m is optimally reallocated among M crops for each farm $j \in \mathbb{R}_+^J$:

$$\text{(B)} \qquad rW(p,w,K,c)^{(2)} = \max_{\{y,x,I,L_m^*,\gamma\}} \{p'y - w'x + W_K(.)'(I - \delta K)\}$$

s.t.

$$\text{(B.1)} \qquad y_m \leq \sum_{j=1}^{J} \gamma_m^j y_m^j, m = 1, \dots, M$$

$$\text{(B.2)} \qquad \sum_{j=1}^{J} \gamma_m^j x^j \leq x_n, m = 1, \dots, M, n = 1, \dots, N$$

$$\text{(B.3)} \qquad \left(I_f - \delta_f K_f\right) \leq \sum_{j=1}^{J} \gamma_m^j \left(I_f^j - \delta_f K_f^j\right), m = 1, \dots, M,\ f = 1, \dots, F$$

(B.4) $\sum_{j=1}^{J} \gamma_m^j G^j \leq G_z, m = 1, \ldots, M,\ z = 1, \ldots, Z$

(B.5) $\sum_{j=1}^{J} \gamma_m^j L_m^j \leq L_m^*, m = 1, \ldots, M$

(B.6) $\bar{L} = \sum_{m=1}^{M} L_m^*, m = 1, \ldots, M$

(B.7) $\sum_{j=1}^{J} \gamma_m^j = 1, m = 1, \ldots, M$

(B.8) $\gamma_m^j \geq 0, m = 1, \ldots, M, j = 1, \ldots, J$

(B.1), (B.2), (B.3), (B.4), (B.7) and (B.8) are equivalent to (A.1), (A.2), (A.3), (A.4), (A.6) and (A.7), respectively. Output-specific land use is endogenised and is thus an explicit choice variable L_m^* in constraint (B.5). Constraint (B.6) ensures that the sum of the optimal land uses is equal to the total land area $\bar{L}$.

Programmes (A) and (B) are linear and thus follow the Data Envelopment Analysis (DEA) approach. DEA assumes convexity of the technology set, as the frontier consists of convex combinations of resource allocations of dominating peers, resulting in a piecewise linear frontier. The convexity assumption is contested less for a production technology with only conventional inputs and outputs (as in problems (A) and (B)) than for a production technology augmented with environmental goods or bads (as is commonly done in the literature to compute environmental efficiency and productivity measures and corresponding shadow prices). However, this assumption may still be strong in the agricultural context, where various types of capital equipment are non-divisible (Ang and Kerstens, 2017). Being the main approach in the economics literature, our paper chiefly focuses on the DEA models. Nonetheless, it is important to point out that convexity of the technology set is *not* a *necessary* condition for our dynamic profit-maximisation problems. Varian (1984) and Kuosmanen (2003) show that static profit maximisation does not require convexity of the technology set. The profit-maximising resource allocations subject to a non-convex technology set can be computed using the Free Disposal Hull (FDH) method (Briec, Kerstens et al., 2004). Adapting this reasoning from a static to a dynamic context, we run such FDH models as a robustness check for non-convexity of the technology set. The FDH models are similar to the DEA models, being the solutions to programmes (A) and (B), but with binary intensity variables (i.e. $\gamma_m^j \in [0,1]$). This adjustment results in mixed-integer programmes by which the dynamic profit-maximising resource allocation is determined by the resource allocation of only one dominating peer.

The gain in current-value profit from optimally reallocating land use is:

(6) $\Delta rW(.) = rW(.)^{(2)} - rW(.)^{(1)}$ where $\Delta rW(.) \geq 0$

The Shannon index for crop diversity $S(L_m, G_{fallow})$ is the environmental good considered in our analysis. It is a function of output-specific land use L_m and fallow land G_{fallow}:

$$(7)\ S(L_m, G_{fallow}) = -\sum_{m=1}^{M}\left[\frac{L_m}{L+G_{fallow}} * \ln\frac{L_m}{L+G_{fallow}}\right] - \frac{G_{fallow}}{L+G_{fallow}} * \ln\frac{G_{fallow}}{L+G_{fallow}}$$

In line with the CAP's '2 or 3 crop rule', an area left fallow is counted as crop land use. Programme (B) seeks for the land allocation under dynamic profit maximisation. We are able to compute the Shannon index for crop diversity associated with the current allocation $S(.)^{(1)}$, on the one hand, and the land allocation under dynamic profit maximisation $S(.)^{(2)}$, on the other. We define the change in the Shannon index for crop diversity due to optimal reallocation of land use as:

$$(8)\ \Delta S(.) = S(.)^{(2)} - S(.)^{(1)} \text{ where } \Delta S(.) \lesseqgtr 0$$

Finally, we assess the trade-off between current-value profit and the Shannon index by the ratio of Eq. (6) to Eq. (8). In line with Sipiläinen and Huhtala (2013), we normalise by total land area:

$$(9)\ \alpha = \frac{-\Delta rW(.)/\Delta S(.)}{10*(L+G_{fallow})}$$

where α is the opportunity cost of the Shannon index as it measures the foregone current-value profit of increasing the Shannon index by 0.1 per unit of land. A positive (negative) α indicates that greater crop diversity decreases (increases) current-value profit. As for shadow pricing by the distance function approach, it indicates a willingness to accept (pay) to increase the Shannon index by 0.1 per unit of land and is expressed in £ per hectare.

A few comments are in order here. The Shannon index for crop diversity increases with the number of crops and evenness of the area covered by the crops. For a given number of crops, a farm can maximise its Shannon index by using an even distribution of crop areas. Although an increase in the Shannon index is generally beneficial in ecological terms, prudence is required in its interpretation. First, being an integrative measure, some information inevitably becomes masked. The Shannon index does not provide information about the exact crop shares. This is particularly relevant for the optimal crop shares under dynamic profit maximisation, where more profitable products (e.g. barley) can be more difficult to sell on the market or constrained by limitations on crop rotation. We therefore also discuss the change in land use corresponding to the optimal change in the Shannon index for crop diversity. Second, the Shannon index is sensitive to scale. A larger area leads in general to a higher species richness and as a result a higher Shannon index for crop diversity. Following Sipiläinen and Huhtala (2013), one may choose between an ecologically meaningful scale and an economically meaningful scale. In line with their study, our application opts for the latter, as we are interested in computing farm-specific opportunity costs of crop diversification. The farm level is also the relevant scale in the '2 or 3 crop rule' recently introduced by the CAP.

By not implementing an environmental good in the production technology, we avoid making questionable assumptions about the production technology and do not predetermine the sign of the opportunity cost. Our approach does not depend on (1) a non-negative relationship between input use and production of the environmental good, (2) a non-negative trade-off between conventional production and production of the environmental good and (3) convexity of the production technology.

The interpretation of the opportunity cost is not exactly the same as the shadow price obtained by exploiting duality. Shadow pricing in the augmented distance function framework is essentially a *marginal* concept which relies on convexity of the environmental technology set. Eq. (9) shows that α should be interpreted as the *average* foregone current-value profit of increasing the Shannon index by 0.1 unit. Our approach is somewhat similar to that of Coelli, Lauwers et al. (2007), who avoid implementing the environmental "bad" (pollutant) in the production technology. They construct "shadow cost estimates" (p. 11) as opportunity costs by calculating the ratio of the difference between costs under minimised pollution and minimised costs, to the difference between minimised pollution and pollution under minimised costs. Throughout this paper, we use the term "opportunity cost" rather than "shadow price" or "shadow cost", as the latter terms may have the connotation of differentiability of the technology set.

3. Data

We use data from the Farm Business Survey (FBS) dataset for the years 2007-2013. The FBS dataset provides farm-level information on economic and physical characteristics for a large sample of English and Welsh farms. We distinguish eight marketable crop outputs (wheat, barley, oats, beans, peas, potatoes and sugar beet, and 'other outputs'[2]), eight variable inputs (seed and planting stock, fertilizer, crop protection, electricity, heating fuel, external labour, management and 'other variable inputs'), two quasi-fixed inputs (buildings and machinery), one fixed output-specific input that can be reallocated (output-specific land) and two fixed non-

[2] The 'other outputs' category consists of outputs that cannot be counted as separate crop types following the CAP's '2 or 3 crop rule'. Although its corresponding land use is assumed to be reallocatable, it does not enter the calculation of the Shannon index for crop diversity.

reallocatable inputs (residual land and family labour). Hired labour and management are expressed in annual working hours. Using price indexes obtained from the EUROSTAT (2015) database, we express the prices of crop outputs, the remaining variable inputs and the investments in quasi-fixed inputs in constant 2007 £. Implicit aggregated quantities are computed for 'other outputs' by using Törnqvist price indexes. All outputs include subsidies, but exclude direct payments. The historical depreciation of quasi-fixed inputs is obtained directly from the FBS dataset and also expressed in constant 2007 £. (Residual) land and family labour are measured respectively in hectares and annual working hours. Variable inputs and fixed non-reallocatable inputs are joint inputs. Note that some variable inputs (*e.g.*, purchased seeds for wheat production) could in theory be output-specific, but that such a specification is not possible due to a lack of data. As residual land contains permanent grassland and other herbaceous forage and fallow land, it improves the nutrient cycling in the soil and benefits the overall production of the marketable outputs. Therefore, these land inputs are also assumed to be joint.

We only consider specialised crop farms in the East of England that do not produce any livestock during the total time period, to obtain a homogenous sample. The FBS rotates the sample in such a way that every farm stays in the sample for five to seven years on average. We use a balanced dataset of 44 observations per year for a period of seven years to maximise the number of analysed years. Table 1 shows the summary statistics of the dataset.

INSERT TABLE 1 AROUND HERE

4. Results

This section is structured as follows. First, we show the main results, where we show the maximum current-value profits obtained using DEA problems (A) and (B), the corresponding Shannon indices and the implied opportunity costs of crop diversification. Then, we conduct several robustness checks to examine the validity of our main results. This section ends with a comparison to the opportunity costs obtained employing Sipiläinen and Huhtala (2013)'s approach, which per usual exploits the distance function's dual relationship to the value function.

4.1. Main Results

DEA problems (A) and (B) are run for each farm in the sample in each year. This procedure controls for shifts of the frontier in time due to technical progress and fluctuating weather conditions. We report the main results in Tables 2-4 and Figure 1. The monetary values are expressed in constant 2007 £ in what follows.

Table 2 shows the actual and maximum current-value profit and corresponding Shannon indices for crop diversity for DEA problems (A) and (B). The actual current-value profit is on average £ 123,900 for all years considered. There is substantial heterogeneity per year, indicating that fluctuating weather conditions play an essential role: while the actual current-value profit reaches on average £ 210,096 in 2012, it is on average only – £ 38,429 in 2009. Assuming that the actual land allocation is fixed, the maximum current-value profit is on average £ 157,407 for DEA problem (A) for all years considered. Allowing for optimal reallocation of land use, the maximum current-value profit is on average £ 195,488 for DEA problem (B). The increase in maximum current-value profit is associated with an increase in the Shannon index for crop diversity from on average 0.85 to 1.13 for all years considered. This pattern is consistent for the whole period.

INSERT TABLE 2 AROUND HERE

Figure 1 illustrates the change in land use in percentage units that corresponds to the optimal change in the Shannon index for crop diversity. It suggests that some land use allocated to wheat, beans and potatoes should shift towards barley, peas, oats and sugar beet. This pattern generally holds, although there are annual fluctuations possibly due to changing market and weather conditions. Note that market conditions and restrictions on crop rotation may prevent farmers from optimally allocating land use. For instance, since wheat is highly marketable, farmers may choose to continue producing at a higher level than the level suggested by our dynamic profit-maximisation model.

INSERT FIGURE 1 AROUND HERE

Table 3 shows the computed opportunity costs of crop diversification obtained by Eq. (9). In what follows, we express the opportunity cost as the average cost (in constant 2007 £) of increasing the Shannon index by 0.1 unit per hectare. The average opportunity cost is - £ 101 for the period, ranging from - £ 244 (in 2009) to £ 34 (in 2007), where only one year shows an average positive opportunity cost. This means that farms are on average willing to pay for crop diversification.

67% of the full sample have a negative opportunity cost for crop diversification. The majority of the farms are thus willing to pay for an increase in the Shannon index for crop diversity. 19% of the calculated opportunity costs are zero, and only 15% are positive. This proportion is consistent for the whole time period.

INSERT TABLE 3 AROUND HERE

Table 4 presents the actual share and share under optimal reallocation of land use according to DEA problem (B) that would have complied with the CAP's '2 or 3 crop rule'. Since all farms in the sample cover more than 30 hectares, the most stringent rule would have been applied. All farms should have produced at least three crops, where the main crop should not have covered more than 75% of the arable land and the two main crops together not more than 95%. 57% of the observations would have complied with the '2 or 3 crop rule'. However, if farms would have optimally reallocated their land use, this share increases to 84%. This pattern is consistent for the whole time period.

INSERT TABLE 4 AROUND HERE

4.2. Robustness Checks

We conduct three robustness checks. First, we investigate the results for the subsample of farms that obtain current-value profits close to their optimal level. Our opportunity cost measure assumes that farms would reallocate land use so as to maximise profit in the long run. Along the lines of Wossink and Swinton (2007), we thus assume that farms are only interested in crop diversification to the extent that it increases current-value profit. However, some farmers may not operate under this behavioural assumption as they are motivated by social and lifestyle goals (Howley, 2015). This robustness check thus focuses on the farms who are likely interested in dynamic profit maximisation. Second, we check the results for the subsample excluding outliers. Such a robustness check is useful as DEA is sensitive to outliers. Third, we investigate the results using the FDH approach, which relaxes the convexity assumption of the technology set. All tables for the robustness checks can be found in the Online Appendix.

4.2.1. Non-Profit-Maximising Behaviour

Table B1 shows the share of farms that have a dynamic profit efficiency of 80% or more for DEA problems (A) and (B). We only take into account the farms that have a positive maximum current-value profit for DEA problems (A) and (B)[3]. 36% of the observations have a dynamic profit efficiency of 80% or more for DEA problem (A). The share ranges from 30% (in 2011) to 52% (in 2007). 26% of the observations have a dynamic profit efficiency of 80% or more for DEA problem (B). The share ranges from 16% (in 2009) to 41% (in 2007).

There are thus many observations with resource allocations deviating greatly from the long-run profit-maximising point. This may indicate that the concerned farms are not long-term profit

[3] Since total land is implemented as a fixed factor, the maximum current-value profit is negative for several observations, especially for bad years such as 2009.

maximisers[4]. Table B2 inspects the opportunity costs for the farms that have a dynamic profit efficiency (*i.e.*, ratio of actual current-value profit to maximum current-value profit) of 80% or more for DEA problems (A) and (B). As for the general results, the computed opportunity costs are on average negative and are only positive on average for one year. Their average opportunity cost is – £ 69 for the period, ranging from – £ 302 (in 2008) to £ 27 (in 2011).

On average 47% of the farms with a dynamic profit efficiency of 80% or more for DEA problem (B) have a negative opportunity cost, while 17% have a positive cost. Only in the year 2011, did the number of farms with a positive opportunity cost exceed the number of farms with a negative opportunity cost. Observe that the dynamically profit efficient farms following DEA problem (B) (36%) have by definition zero opportunity cost of crop diversification, as their land allocation should not be changed.

Table B3 shows the actual share and share under optimal reallocation of land use according to DEA problem (B) that would have complied with the CAP's '2 or 3 crop rule' for the farms with a dynamic profit efficiency of 80% or more. 57% of these observations would have complied with the '2 or 3 crop rule'. If farms would have optimally reallocated their land use, this share increases to 75%. This pattern is consistent for the whole time period (except for the year 2010, where the estimated share for DEA problem (B) is equal to the actual share).

4.2.2. Outliers

Following Oude Lansink and Silva (2004), we truncate the original sample by excluding observations that are at least two standard deviations from the mean, to check the robustness to outliers. Table C1 shows the opportunity costs of this truncated subsample. The resulting opportunity costs are on average negative for each year. Their average opportunity cost is – £ 28 for the period, ranging from – £ 91 (in 2013) to – £ 3 (in 2010). 43% of the farms from the truncated subsample have a negative opportunity cost and 17% a positive cost.

Table C2 reveals that more farms from the truncated subsample would comply with the '2 or 3 crop rule' if they would have optimally reallocated their land use. Dynamic profit maximisation allowing for reallocation of land use leads to an increase in compliance from 57% to 84%. This pattern is consistent for the whole period.

4.2.3. Non-Convexity

[4] Obtaining the shadow price by using the dual relationship of the value function to the distance function faces a similar issue, as this depends on an arbitrary projection to the technological frontier. This is particularly a problem for very inefficient farms where the shadow price is sensitive to the choice of the directional vector or orientation.

Table D1 shows the opportunity costs of crop diversification using the FDH model. The resulting opportunity costs are on average £ 35 considering the whole period, with a minimum of – £ 21 (in 2008) and a maximum of £ 77 (in 2010). 31% (15%) of the farms have a negative (positive) opportunity cost. This pattern holds for the whole period. Note that the FDH model allows for non-convexity of the technology set, but results in reduced detection of non-optimising farms. Therefore, the share of farms with a zero opportunity cost is high (55%).

Table D2 shows the actual share and share under optimal reallocation of land use according to problem (B) adjusted for non-convexity that would have complied with the CAP's '2 or 3 crop rule'. Dynamic profit maximisation allowing for reallocation of land use leads to an increase in compliance from 57% to 67%. This pattern is consistent for the whole period. Again, these gains are somewhat more modest due to a lower detection of non-optimising farms inherent to the FDH model.

4.3. Comparison to Usual Shadow-Pricing Approach

The prevailing negative opportunity costs contrast with the imposed non-negative shadow prices of the usual approach of modelling environmental goods as conventional outputs in a distance function framework. Sipiläinen and Huhtala (2013) also computed the opportunity cost of the Shannon index for crop diversity using the distance function's dual relationship to the value function. They found an average opportunity cost between £ 12 and £ 45 (in constant 2007 terms) per 0.1 ha for a sample of Finnish cereal farms. We apply their approach for comparison (see Appendix E) and show the results in table 5. We run their model for each farm in the sample in each year to ensure comparability with our proposed approach. The estimated shadow price is £ 79 for the period, ranging from £ 22 (in 2008) to £ 212 (in 2013). As expected, these results are non-negative, which contradict the results of our introduced opportunity cost measure.

INSERT TABLE 5 AROUND HERE

5. Discussion

Our main finding is that dynamic profit-maximisation allowing for optimal land reallocation is generally associated with an increase in the Shannon index for crop diversity. The opportunity cost of crop diversification is mostly negative and most farms would have complied with the '2 or 3 crop rule' recently imposed by the CAP if they had optimally reallocated their land use. These results are robust to excluding observations far from the dynamic profit-maximising point, excluding outliers, and allowing non-convexity of the technology set. Negative

opportunity costs could not have been obtained by exploiting the distance function's dual relationship to the value function as commonly done in the literature. Our results are in line with the conceptual and empirical work of respectively Wossink and Swinton (2007) and Sauer and Wossink (2013), who argue that many farms would be willing to pay to increase the provision of environmental goods as its relationship with conventional production is not purely competitive. This coincides with the ecological perspective that environmental measures may be needed for long-term economic benefits.
Since nonparametric models are in essence deterministic, we have implicitly assumed that farms can perfectly foresee the outcomes of their production decisions. However, there is in reality considerable uncertainty in agricultural production due to unforeseen weather conditions. As a result, our model may compare farms that have different output realisations due to different 'States of Nature' (Quiggin and Chambers, 2006). We partially control for this issue by running the DEA models per year. For instance, since 2009 clearly marks a year with a bad State of Nature, the reference technology only consists of observations for the year 2009. One could consider controlling for this issue even more by also running the DEA models per government office region. However, subdividing our sample into smaller subsamples leads to dimensionality problems given the large number of inputs, outputs and net investments in dynamic factors compared to the relatively low number of observations. Moreover, all farms considered are located in the East of England, which is a fairly homogeneous region with similar weather conditions. This ensures that the bias due to different States of Nature at the time of production is small. Note that our findings are persistent for each of the seven years considered, hold for the subsample of farms with a dynamic profit efficiency of 80% or more, is robust to excluding extreme observations, and hold for a non-convex production technology.

In the light of the 'Green Direct Payment' measure introduced recently by the CAP, we may reflect on whether the relative robustness of our results translates into predictive power. On the one hand, the predicted potential is possibly underestimated. We have aggregated spring and winter crops as these belong to the same species. However, according to the '2 or 3 crop rule', spring and winter crops can be counted as separate crops. Also fallow land can be counted separately according to this rule. Although we take this into account in our calculations, these are assumed to be non-reallocatable inputs that jointly contribute to the production of marketable outputs. In addition, it is plausible that farmers use crop diversification as a risk-reducing mechanism, even if it would lead to lower rather than higher expected profits (Di Falco and Chavas, 2008; Di Falco and Chavas, 2009). On the other hand, there are also several reasons to believe that the predicted potential is overestimated. There is plenty of evidence of persistent inefficient behaviour due to inherent non-economic objectives (Howley, 2015) or persistent technical inefficiency (Emvalomatis, Stefanou et al., 2011). Such dynamic profit inefficiency is also present in the current study. Moreover, although dynamic profit maximisation would lead to a shift to more profitable products such as barley, this remains constrained by market conditions and limitations on crop rotation. In summary, although our findings suggest no general justification of subsidisation of crop diversification, we remain cautious about the predictive power of our model.

6. Conclusions

Distance functions are increasingly being augmented with environmental goods treated as outputs to assess the trade-off between environmental goods and outputs. A common approach to evaluate the opportunity cost of providing an environmental good is the exploitation of the distance function's dual relationship to the value function. However, this approach may rely on problematic assumptions about the environmental goods' axiomatic properties. In particular, it is assumed that an environmental good can be treated as a conventional, strongly disposable output and that its shadow price is as a result always non-negative. Moreover, the convexity assumption of the augmented environmental technology set is necessary to ensure that the output distance function's dual relationship to the revenue function holds.

Focusing on crop diversification, this paper develops an opportunity cost measure that overcomes these drawbacks for a sample of English cereal farms covering the years 2007-2013. Using a nonparametric model, we assess the extent to which reallocation of land use can increase current-value profit. As this increase is linked to a change of the Shannon index for crop diversity, this allows us to express the opportunity cost of crop diversification in terms of foregone current-value profit. Our proposed measure relies solely on standard axiomatic properties of conventional inputs and outputs, does not critically depend on convexity of the technology set, and is consistent with the behavioural assumption of dynamic profit-maximisation. Our results are robust to excluding observations far from the dynamic profit-maximising point, excluding outliers, and relaxing the convexity assumption of the technology set.

The results show that the opportunity cost of crop diversification is mostly negative. This is an interesting outcome, as distance functions augmented with environmental goods treated as outputs implicitly assume that shadow prices of environmental goods are always non-negative. The results also indicate that optimal reallocation of land use, which would have maximised dynamic profit, would have led to increased compliance with the CAP's recently introduced '2 or 3 crop rule'. These results may be interpreted that crop diversification does not generally justify subsidies, suggesting a reconsideration of the financial mechanism of the CAP's Green Direct Payment measure. However, we remain cautious about the general policy implications of the results, for we have focused on a sample of specialised farms in a particular region (East of England). Additionally, we have observed high dynamic profit inefficiency, which is likely to persist after the introduction of the '2 or 3 crop rule'. Finally, market conditions and limitations on crop rotation may limit shifts to the dynamic profit-maximising land allocation.

We have several suggestions for future research. First, there is a demand from policy makers to develop a holistic sustainability measure which incorporates environmental goods and bads in a rigorous way. Understanding the trade-offs among inputs, outputs, and environmental goods and bads is essential to this end. Our measure has explicitly separated the environmental good from the production technology. There could be other ways to realistically model environmental goods and bads within the production technology. Murty, Russell et al. (2012) develop distance functions that specifically model the pollution-generating inputs. It may be worthwhile to also model the inputs that generate environmental goods. Second, our measure can be augmented by taking into account spatial heterogeneity, which occurs due to different environmental circumstances and market conditions (Polasky, Nelson et al., 2008; Nelson, Mendoza et al., 2009). Third, our measure can be extended by accounting for risk along the lines of Chavas and Di Falco (2012), since crop diversification is an important mechanism of risk reduction, potentially at the expense of expected profits.

On-Line Appendix A

Following Kuosmanen, Kortelainen et al. (2010), we solve the following linear problem to find values for $W_K(.)$ for each farm $j \in \mathbb{R}_+^J$:

(C) $\min_{\{p,w,v,W_K,\rho\}} \rho$

s.t.

(C.1) $\rho \geq \left(p'y - w'x - v'L + W_K{}'(I - \delta K)\right) - \left(p'y_i - w'x_i - v'L_i + W_K{}'(I_i - \delta_i K_i)\right), i = 1, \dots, J$

(C.2) $p'g_y + w'g_x + v'g_L + W_K{}'g_I = 1, \left(g_y, g_x, g_I, g_L\right) = \left(\frac{1}{p}, 0{,}0{,}0\right)$

(C.3) $p'g_y + w'g_x + v'g_L + W_K{}'g_I = 1, \left(g_y, g_x, g_I, g_L\right) = \left(0, \frac{1}{w}, 0{,}0\right)$

(C.4) $p \geq 0$

(C.5) $w \geq 0$

(C.6) $v \geq 0$

(C.7) $W_K \geq 0$

where $y \in \mathbb{R}_+^1$ is the aggregated output vector, $x \in \mathbb{R}_+^1$ is the aggregated variable input vector, $K_t \in \mathbb{R}_+^F$ is the initial capital stock vector, $I \in \mathbb{R}_+^F$ is the investment vector, $L \in \mathbb{R}_+^2$ is the vector of fixed factors consisting of total agricultural land area and family labor, $p \in \mathbb{R}_+^1$ is the vector of aggregated output prices, $w \in \mathbb{R}_+^1$ is the vector of aggregated input prices, $v \in \mathbb{R}_+^2$ is the vector of fixed factor prices, $c \in \mathbb{R}_+^F$ is the vector of capital prices, $W_K \in \mathbb{R}_+^F$ is the vector of shadow values of capital, δ is a diagonal $F \times F$ matrix of depreciation rates $\delta_f > 0, f, \dots, F$ $\left(g_y, g_x, g_I, g_L\right)$ is the directional vector in terms of outputs, inputs, investment and fixed factors. Outputs and inputs are aggregated by Törnqvist price indexes to reduce dimensionality. This means that quality differences are assumed to be revealed by the implicit quantity (Cox and Wohlgenant, 1986). This model is run per year. It also solves for the prices $v \in \mathbb{R}_+^2$ of the vector of fixed factors (total land and family labour). By setting $\left(g_y, g_x, g_L, g_I\right) = \left(\frac{1}{p}, 0{,}0{,}0\right)$ and $\left(g_y, g_x, g_L, g_I\right) = \left(0, \frac{1}{w}, 0{,}0\right)$ in respectively C.2 and C.3, we ensure that L is treated as a vector of fixed factors and the known information on output and input prices is incorporated in the model. The farm-specific values for W_K are plugged into DEA problems (A) and (B).

On-Line Appendix B

Table B1. Share of farms with a dynamic profit efficiency of 80% or more for DEA problems (A) and (B), 2007-2013

Year	Share for DEA problem (A)	Share for DEA problem (B)
2007	52%	41%
2008	43%	39%
2009	30%	16%
2010	32%	18%
2011	30%	27%
2012	32%	20%
2013	34%	23%
Period	36%	26%

Table B2. Opportunity costs of the Shannon index for crop diversification per 0.1 ha for farms with a dynamic profit efficiency of 80% or more for DEA problem (B) using the proposed method, 2007-2013

Year	Number of farms	Average (in constant 2007 £)	Std. Dev. (in constant 2007 £)	Share		
				Negative	0	Positive
2007	18	-17	169	39%	50%	11%
2008	17	-302	1342	59%	29%	12%
2009	7	-1	3	29%	71%	0%
2010	8	-14	42	38%	38%	25%
2011	12	27	47	33%	25%	42%
2012	9	-12	46	44%	22%	33%
2013	10	-22	24	80%	20%	0%
Period	81	-69	618	47%	36%	17%

Table B3. Actual share and share under optimal reallocation of land use according to DEA problem (B) that would have complied with the CAP's '2 or 3 crop rule' for farms with a dynamic profit efficiency of 80% or more, 2007-2013

Year	Actual share	Estimated share for DEA problem (B)	Gains from optimal reallocation in percentage units
2007	61%	72%	+11%
2008	47%	71%	+24%
2009	57%	86%	+19%
2010	63%	63%	+0%
2011	58%	83%	+25%
2012	56%	78%	+22%
2013	60%	80%	+20%
Period	57%	75%	+17%

On-Line Appendix C

Table C1. Opportunity costs of the Shannon index for crop diversification per 0.1 ha for subsample excluding outliers, 2007-2013

Year	Number of farms	Average (in constant 2007 £)	Std. Dev. (in constant 2007 £)	Share		
				Negative	0	Positive
2007	42	-9	105	55%	26%	19%
2008	43	-25	144	72%	19%	9%
2009	43	-15	210	77%	19%	5%
2010	41	-3	75	59%	24%	17%
2011	43	-42	163	58%	19%	23%
2012	43	-28	240	65%	16%	19%
2013	43	-91	174	81%	12%	7%
Period	298	-28	169	67%	19%	14%

Table C2. Actual share and share under optimal reallocation of land use according to DEA problem (B) that would have complied with the CAP's '2 or 3 crop rule' for subsample excluding outliers, 2007-2013

Year	Actual share	Estimated share for DEA problem (B)	Gains in share from optimal reallocation in percentage units
2007	50%	76%	+26%
2008	51%	88%	+37%
2009	60%	98%	+37%
2010	56%	80%	+24%
2011	53%	72%	+29%
2012	58%	84%	+26%
2013	67%	91%	+23%
Period	57%	84%	+28%

On-Line Appendix D

Table D1. Opportunity costs of the Shannon index for crop diversification per 0.1 ha using the proposed method adjusted for non-convexity, 2007-2013

Year	Number of farms	Average (in constant 2007 £)	Std. Dev. (in constant 2007 £)	Share		
				Negative	0	Positive
2007	44	13	164	23%	55%	23%
2008	44	-35	286	27%	57%	16%
2009	44	-21	97	39%	39%	23%
2010	44	77	639	39%	55%	7%
2011	44	16	184	34%	57%	9%
2012	44	23	202	25%	64%	11%
2013	44	70	532	27%	57%	16%
Period	308	21	354	31%	55%	15%

Table D2. Actual share and share under optimal reallocation of land use according to problem (B) adjusted for non-convexity that would have complied with the CAP's '2 or 3 crop rule'

Year	Actual share	Estimated share for problem (B) adjusted for non-convexity	Gains from optimal reallocation in percentage units
2007	52%	57%	+5%
2008	52%	64%	+11%
2009	61%	75%	+14%
2010	57%	73%	+16%
2011	55%	66%	+11%
2012	57%	66%	+9%
2013	68%	70%	+2%
Period	57%	67%	+10%

On-Line Appendix E

We exploit the directional distance function's dual relationship to the profit function by solving a minimax problem similar to linear program (C) in line with Kuosmanen, Kortelainen et al. (2010). We solve the following linear problem to find shadow price u for each farm $j \in \mathbb{R}_{+}^{J}$:

(D) $\min_{\{p,w,v,u,\theta\}} \theta$

s.t.

(D.1) $\theta \geq \left(p'y - w'x - v'L + u'S(.)^{(1)}\right) - \left(p'y_i - w'x_i - v'L_i + u'S(.)^{(1)}\right), i = 1, \dots, J$

(D.2) $p'g_y + w'g_x + v'g_L + u'g_S = 1, \left(g_y, g_x, g_L, g_S\right) = \left(\frac{1}{p}, 0,0,0\right)$

(D.3) $p'g_y + w'g_x + v'g_L + u'g_S = 1, \left(g_y, g_x, g_L, g_S\right) = \left(0, \frac{1}{w}, 0,0\right)$

(D.4) $p \geq 0$

(D.5) $w \geq 0$

(D.6) $v \geq 0$

(D.7) $u \geq 0$

where $y \in \mathbb{R}_{+}^{1}$ is the aggregated output vector, $x \in \mathbb{R}_{+}^{1}$ is the aggregated variable input vector, $L \in \mathbb{R}_{+}^{2}$ is the vector of fixed factors consisting of total agricultural land area and family labour, $S(.)^{(1)}$ is the Shannon index for crop diversity computed by Eq. (9), $p \in \mathbb{R}_{+}^{1}$ is the vector of aggregated output prices, $w \in \mathbb{R}_{+}^{1}$ is the vector of aggregated input prices, $v \in \mathbb{R}_{+}^{2}$ is the vector of fixed factor prices, $u \in \mathbb{R}_{+}^{1}$ is the vector of shadow values of capital, δ is a diagonal $F \times F$ matrix of depreciation rates $\delta_f > 0, f, \dots, F$. $\left(g_y, g_x, g_L, g_S\right)$ is the directional vector in terms of outputs, inputs, fixed factors and the Shannon index for crop diversity. Outputs and inputs are aggregated by Törnqvist price indexes to reduce dimensionality. This means that quality differences are assumed to be revealed by the implicit quantity (Cox and Wohlgenant, 1986). This model is run per year. It also solves for the prices $v \in \mathbb{R}_{+}^{2}$ of the vector of fixed factors (total land and family labor). By setting $\left(g_y, g_x, g_L, g_S\right) = \left(\frac{1}{p}, 0,0,0\right)$ and $\left(g_y, g_x, g_L, g_S\right) = \left(0, \frac{1}{w}, 0,0\right)$ in respectively C.2 and C.3, we ensure that L is treated as a vector of fixed factors and the known information on output and input prices is incorporated in the model.

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Tables

Table 1. Descriptive statistics of the dataset (308 observations for 44 cereal farms), 2007-2013

Variables	Unit	Mean	Std. Dev.
Outputs			
Wheat	Constant 2007 £	173,175	242,325
Barley	Constant 2007 £	7,815	16,023
Oats	Constant 2007 £	3,583	9,818
Beans	Constant 2007 £	4,242	14,516
Peas	Constant 2007 £	8,184	31,342
Potatoes	Constant 2007 £	51,797	75,696
Sugar beet	Constant 2007 £	10,462	21,210
Other outputs	Constant 2007 £	3,630	18,483
Output-specific land			
Wheat	Hectares	154	199
Barley	Hectares	10	19
Oats	Hectares	5	13
Beans	Hectares	6	14
Peas	Hectares	8	30
Potatoes	Hectares	51	65
Sugar beet	Hectares	6	12
Other outputs	Hectares	3	12
Variable inputs			
Seed and planting stock	Constant 2007 £	28,186	41,084
Fertilizer	Constant 2007 £	72,226	79,435
Crop protection	Constant 2007 £	73,105	87,139
Electricity	Constant 2007 £	2,995	6,091
Heating fuel	Constant 2007 £	1,140	2,396
External labor	Annual working hours	2,829	3,927
Management	Annual working hours	16	114
Other variable inputs	Constant 2007 £	9,714	14,144
Investments			
Buildings	Constant 2007 £	6,566	23,596
Machinery	Constant 2007 £	54,093	88,128
Historical depreciation			
Buildings	Constant 2007 £	6,622	10,782
Machinery	Constant 2007 £	31,078	38,539
Fixed non-reallocatable inputs			
Grassland and other herbaceous forage	Hectares	15	34
Fallow land	Hectares	2	7
Family labour	Annual working hours	1,865	822

Table 2. Actual and maximum current-value profit and corresponding Shannon indexes for crop diversity for DEA problems (A) and (B), 2007-2013

Year	Actual current-value profit (in constant 2007 £)	Actual Shannon index for crop diversity	Maximum current-value profit for DEA problem (A) (in constant 2007 £)	Maximum current-value profit for DEA problem (B) (in constant 2007 £)	Shannon index for crop diversity for DEA problem (B)
2007	154,483 (314,419)	0.87 (0.34)	170,212 (310,268)	195,978 (324,841)	1.10 (0.37)
2008	120,307 (173,665)	0.81 (0.35)	140,512 (168,810)	175,024 (180,673)	1.15 (0.33)
2009	- 38,429 (126,077)	0.88 (0.34)	5,724 (100,200)	51,696 (105,261)	1.29 (0.25)
2010	122,038 (220,333)	0.85 (0.41)	144,279 (217,925)	178,307 (229,371)	1.16 (0.40)
2011	176,152 (272,026)	0.82 (0.34)	225,998 (271,740)	278,024 (294,843)	0.96 (0.26)
2012	210,096 (428,709)	0.82 (0.33)	270,091 (421,990)	304,165 (425,447)	1.06 (0.34)
2013	122,651 (206,530)	0.89 (0.38)	145,034 (200,918)	185,223 (214,574)	1.19 (0.31)
Period	123,900 (273,035)	0.85 (0.35)	157,407 (269,026)	195,488 (279,285)	1.13 (0.34)

Table 3. Opportunity costs of the Shannon index for crop diversification per 0.1 ha using the proposed method, 2007-2013

Year	Number of farms	Average (in constant 2007 £)	Std. Dev. (in constant 2007 £)	Share		
				Negative	0	Positive
2007	44	34	290	55%	25%	20%
2008	44	-149	830	73%	18%	9%
2009	44	-244	1531	77%	18%	5%
2010	44	-21	159	59%	23%	18%
2011	44	-110	481	59%	18%	23%
2012	44	-105	564	66%	16%	18%
2013	44	-113	257	80%	11%	9%
Period	308	-101	730	67%	19%	15%

Table 4. Actual share and share under optimal reallocation of land use according to DEA problem (B) that would have complied with the CAP's '2 or 3 crop rule', 2007-2013

Year	Actual share	Estimated share for DEA problem (B)	Gains in share from optimal reallocation
2007	52%	77%	+25%
2008	52%	89%	+36%
2009	61%	98%	+36%
2010	57%	80%	+23%
2011	55%	73%	+18%
2012	57%	82%	+25%
2013	68%	93%	+25%
Period	57%	84%	+27%

Table 5. Opportunity costs of the Shannon index for crop diversification per 0.1 ha using the directional distance function approach, 2007-2013

Year	Number of farms	Average (in constant 2007 £)	Std. Dev. (in constant 2007 £)	Share		
				Negative	0	Positive
2007	44	49	125	0	27%	73%
2008	44	22	68	0	52%	48%
2009	44	37	50	0	48%	52%
2010	44	65	151	0	64%	36%
2011	44	110	330	0	66%	34%
2012	44	61	169	0	16%	84%
2013	44	212	941	0	61%	39%
Period	308	79	391	0	48%	52%

Figures

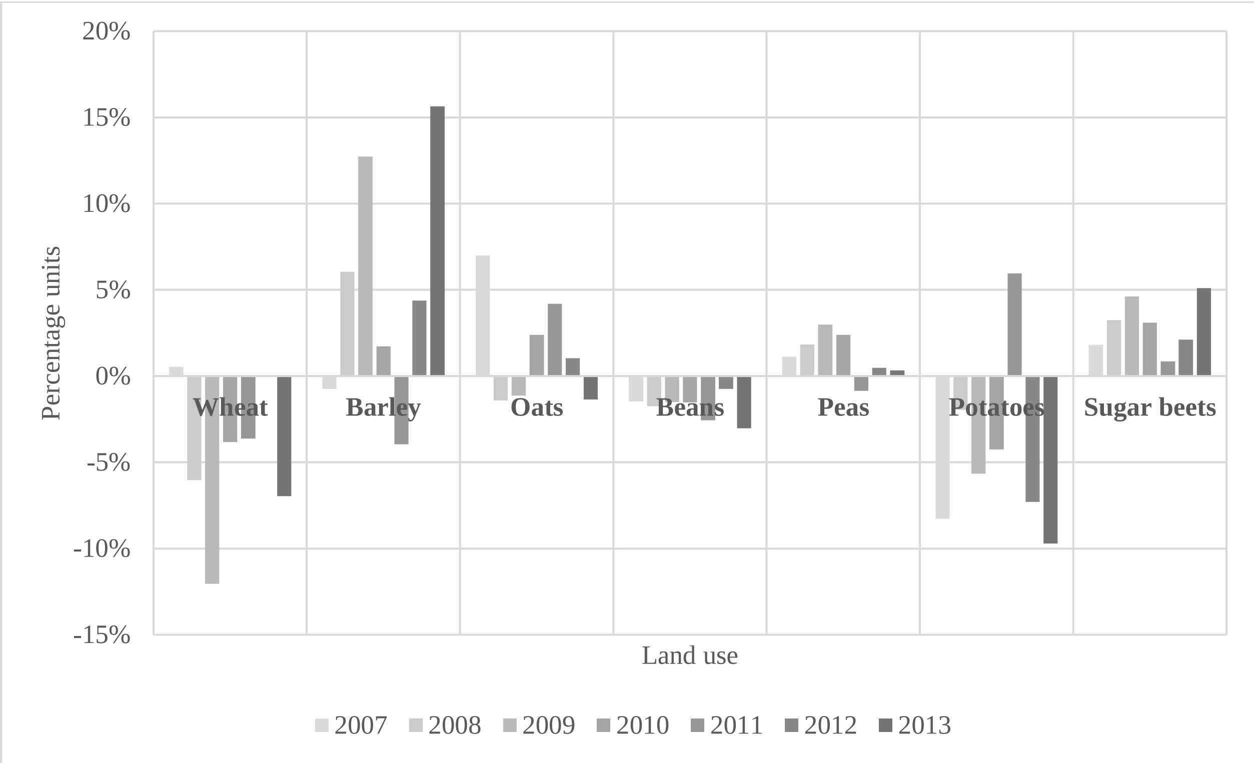

Figure 1. Change in land use required for dynamic profit maximisation, 2007-2013 (in percentage units)